

Habitat capacity index for Chinook Salmon parr in the Grande Ronde Basin



Catherine Creek (Southern Cross),
Photo by Connor Stone (GRMW)

Grande Ronde Life Cycle
Modeling Workshop

November 16, 2021

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Organization:
Columbia River Inter-Tribal
Fish Commission (CRITFC)

Funded By:



Background



Fish habitat in the upper Grande Ronde basin has been heavily degraded by land use including timber harvest, agriculture, mining, grazing, and beaver trapping.

These impacts, combined with hydropower, over-harvest, and other factors led to the listing of local Spring Chinook Salmon and steelhead populations under the Endangered Species Act and subsequent efforts to restore habitat conditions and improve survival throughout the life cycle.

Habitat limiting factors for salmon recovery include:

- 1) **Elevated summer water temperature,**
- 2) Diminished summer streamflow,
- 3) Reduced channel complexity and structure,
- 4) Reduced floodplain connectivity, and
- 5) Degraded riparian conditions

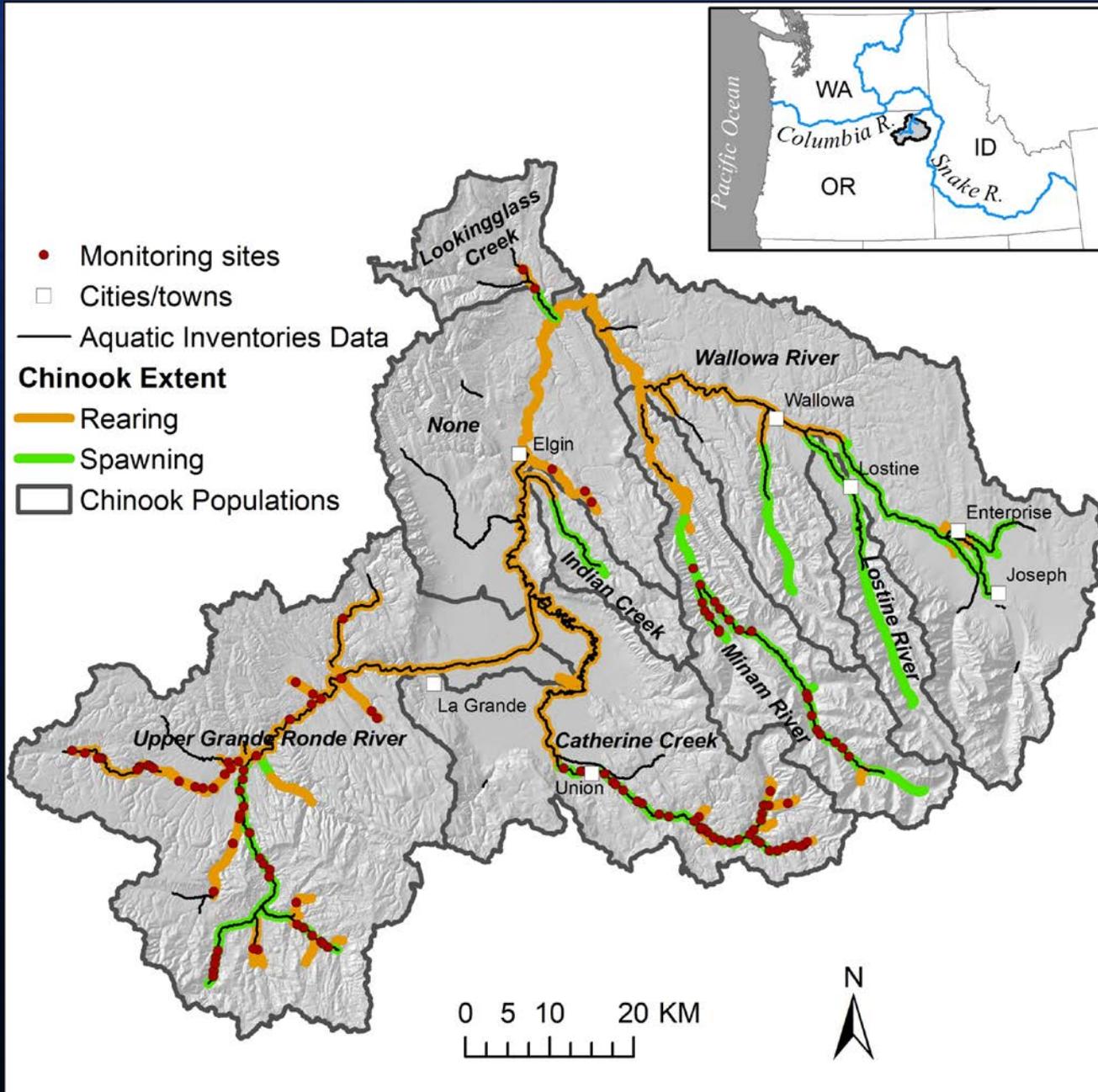
Tools are needed to evaluate past and future impacts of restoration actions on fish populations so that limited restoration dollars can be used most effectively to recover our salmon populations.



Objectives

1. Develop a model using local empirical data describing the relationship between Chinook summer parr abundance and stream habitat conditions
2. Extrapolate model predictions across the Chinook-bearing stream network in the upper Grande Ronde and Wallowa River basins using spatially continuous habitat data
3. Use model predictions to derive an index of habitat capacity (i.e., weighted usable habitat) that can be utilized in a life cycle model to evaluate how alternative management scenarios may impact future salmon population viability.

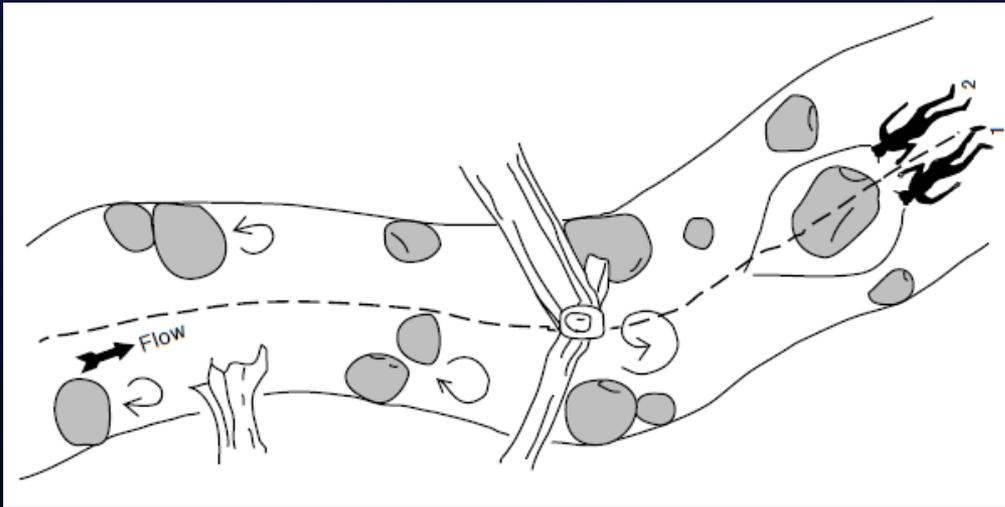
Study Area



- 121 paired fish and habitat survey sites
- Sites selected randomly using GRTS
- Site length $\approx 20 \times$ bankfull width
- 7 years (2011-2017)
- 294 total observations

Snorkel Surveys

- Snorkel surveys conducted by CRITFC and ODFW using protocol from White et al. (2012; CRITFC technical report)
- Counted Chinook, *O. mykiss*, and Bull Trout by size class and noted presence/absence of other species
- Individual counts by channel unit (i.e., pool, riffle, run)



Correcting for Partial Detectability in Snorkel Surveys

The problem:

- 1) Snorkel counts usually represent a fraction of the true number of fish present.
- 2) Habitat conditions (e.g., water depth, visibility) can influence detection probability and lead to biased abundance estimates if not accounted for.

The solution:

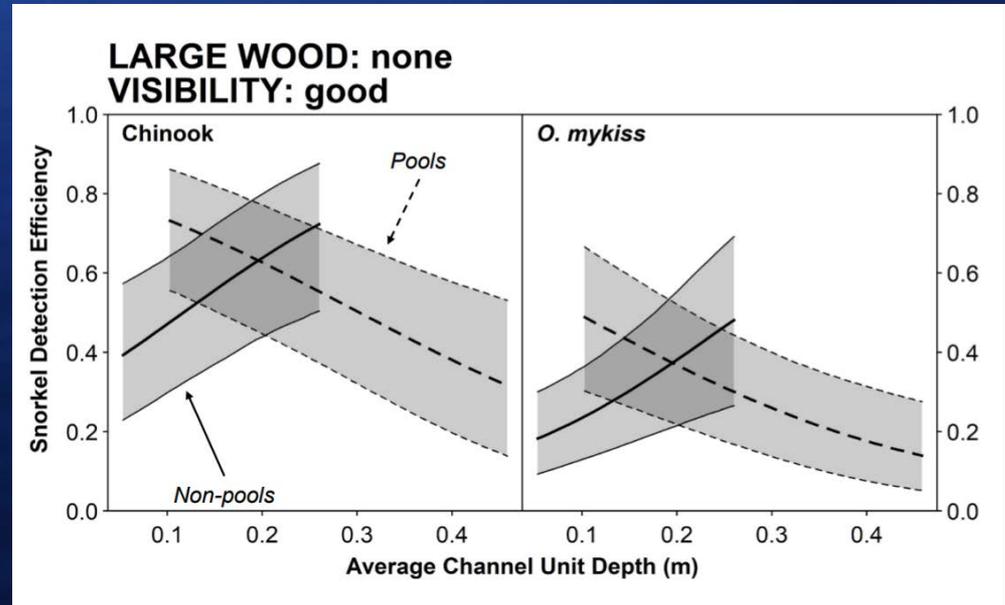
- 1) Estimate snorkel detection probability
- 2) Expand snorkel counts using predicted detection probability to estimate true abundance

Snorkel Efficiency Study (2012, 2015):

- Led by ODFW with assistance from CRITFC
- ~ 100 paired snorkel and mark-recapture abundance estimates in the Grande Ronde basin

Analysis (2021):

- Led by Ben Staton, CRITFC
- Bayesian model accounting for uncertainty in both snorkel counts and mark-recapture estimates
- Accounts for mechanistic links between local conditions and detectability



From: Staton et al. (*in review*) *Fisheries Research*



Develop fish-habitat model for Chinook parr density

Zero-inflated Negative Binomial Model:

- Appropriate for count data
- Accounts for large amount of among-observation variability (over-dispersion)
- Zero-inflated component required to accommodate the excessive zero-valued observations (~36% of total observations)

Global (fully-parameterized) conditional model:

$\text{Log}(\text{count}/100\text{m}) = \text{Spawner abundance} + \text{Gradient} + \text{Gradient}^2 + \text{Log}(\text{Large wood frequency}) + \text{Log}(\text{Mean summer flow}) + \text{Water temperature} + \text{Pool frequency} + \text{River complexity index} + (\text{Site}) + (\text{Year})$

Global zero model:

$\text{Logit}(\text{probability of zero count}) = \text{Spawner abundance} + \text{Chinook extent}$

Model fitting in glmmTMB package in R

Model selection using dredge in MuMIn package in R

Model Selection

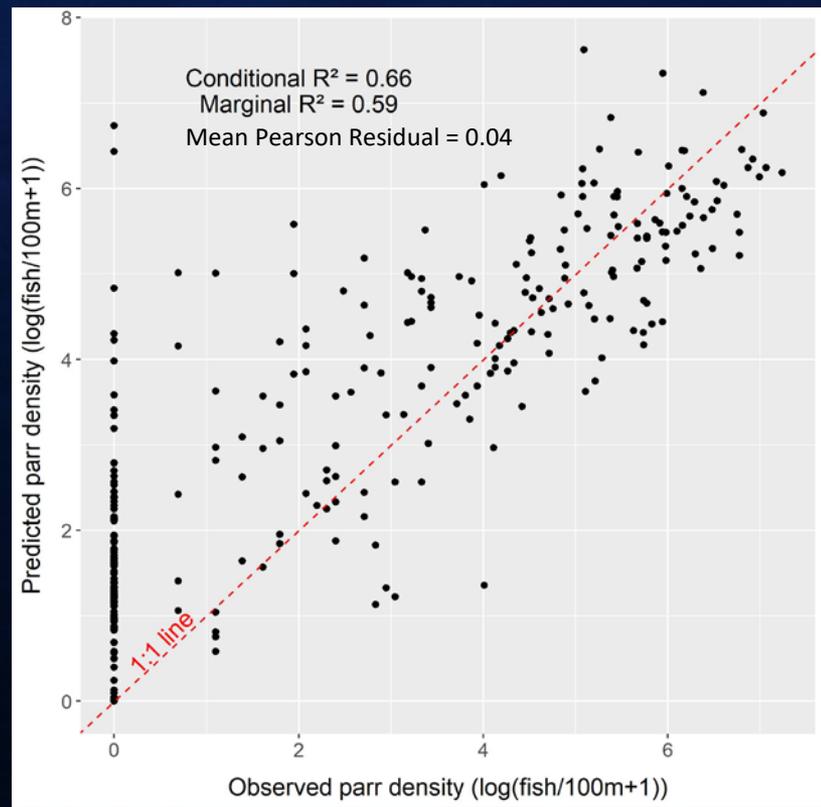
Conditional model fixed effects									Zero-inflated fixed effects								
Int	LogLWFreq	LogMSQ	MWMT	Grad	Grad2	PIFreq	SpawnStd	RCI	zi(Int)	CurSpawn	SpawnStd	DF	AICc	ΔAICc	Weight	R _m ²	R _c ²
5.575	0.322	0.764	-0.155	1.131	-0.375	0.039	0.456	NA	1.484	+	-0.857	14	2440.5	0.0	0.64	0.59	0.66
5.572	0.322	0.765	-0.155	1.115	-0.372	0.038	0.454	0.021	1.483	+	-0.858	15	2442.6	2.1	0.22	0.59	0.66
6.153	NA	0.727	-0.173	1.354	-0.414	0.055	0.438	NA	1.475	+	-0.846	13	2445.0	4.5	0.07	0.58	0.68
6.601	0.453	0.740	-0.175	0.781	-0.313	NA	0.472	NA	1.497	+	-0.865	13	2446.8	6.3	0.03	0.57	0.65
6.143	NA	0.728	-0.173	1.344	-0.411	0.054	0.435	0.017	1.475	+	-0.846	14	2447.2	6.7	0.02	0.58	0.68
6.529	0.442	0.745	-0.176	0.761	-0.307	NA	0.464	0.061	1.496	+	-0.867	14	2448.1	7.6	0.01	0.58	0.65

Best fitting model:

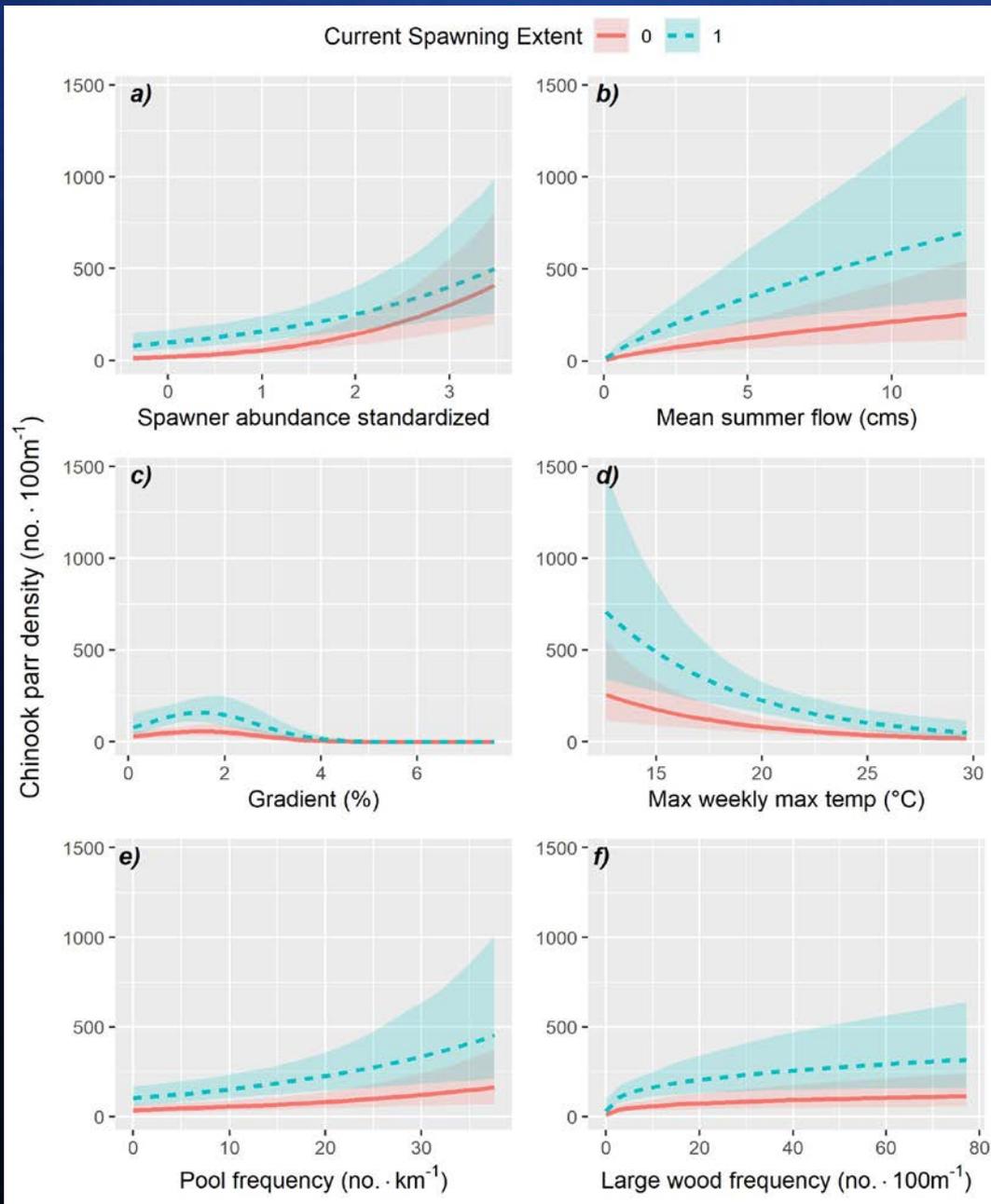
$$\text{Log}(\text{count}/100\text{m}) = \text{Spawner abundance} + \text{Gradient} + \text{Gradient}^2 + \text{Log}(\text{Large wood frequency}) + \text{Log}(\text{Mean summer flow}) + \text{Water temperature} + \text{Pool frequency} + (\text{Site}) + (\text{Year})$$

Best fitting zero model:

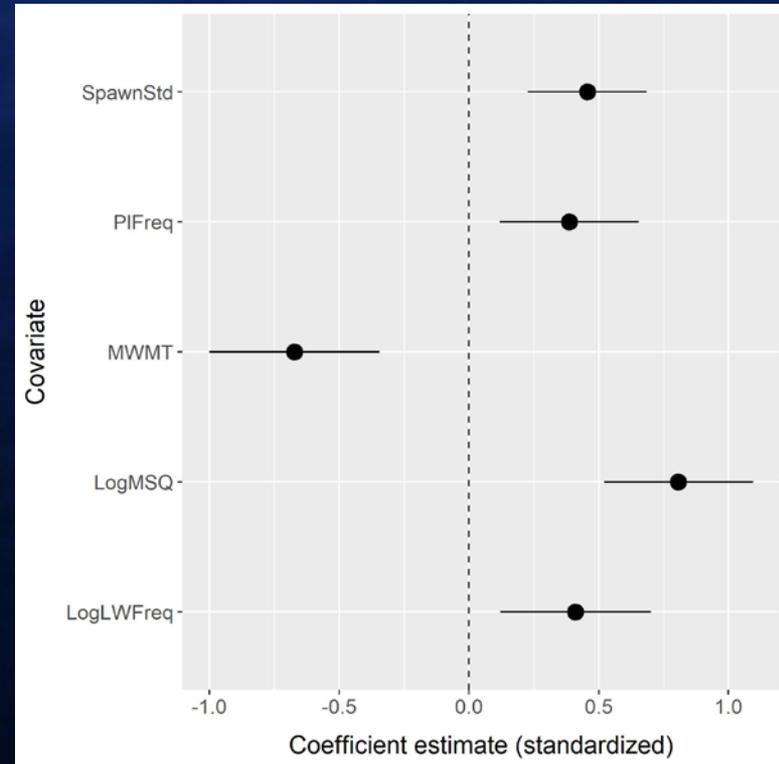
$$\text{Logit}(\text{probability of zero count}) = \text{Spawner abundance} + \text{Chinook extent}$$



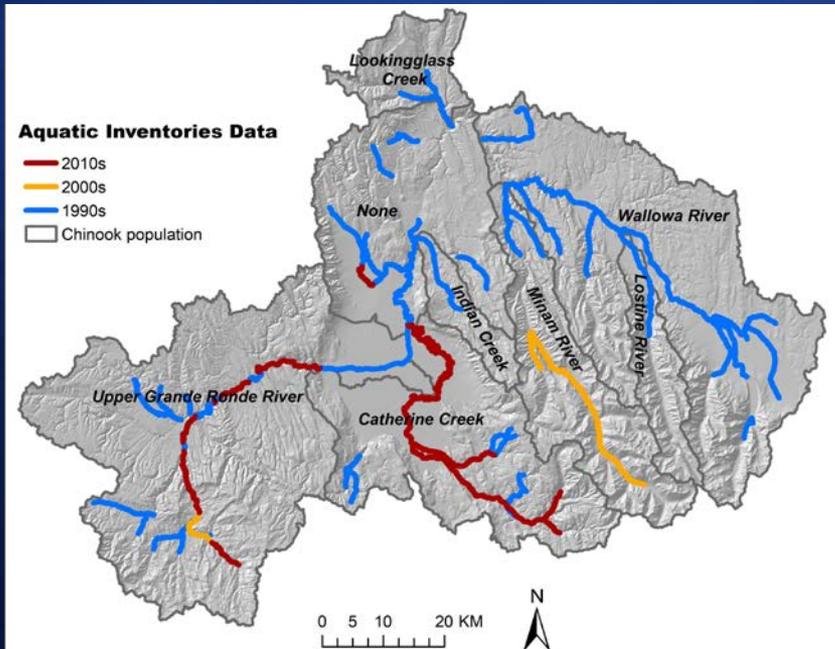
Model Effects



Effect Size



Extrapolating Density Predictions Across the Stream Network

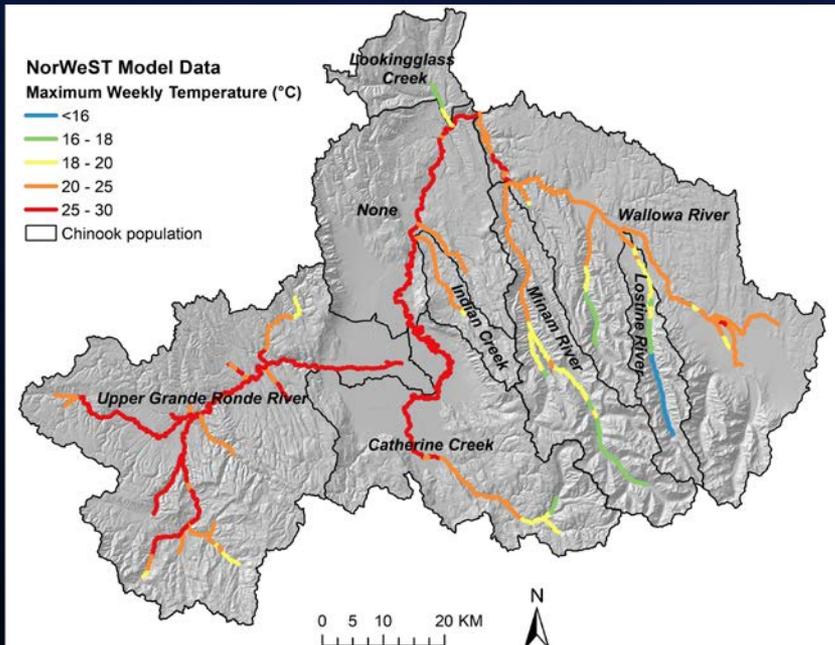


ODFW's Aquatic Habitat Inventories (1991-2020; Moore et al. 2019)

- Pool frequency
- Large wood frequency

NorWeST Water Temperature Model (1993-2015; Isaak et al. 2017)

- Maximum weekly maximum temperature ($^{\circ}\text{C}$)



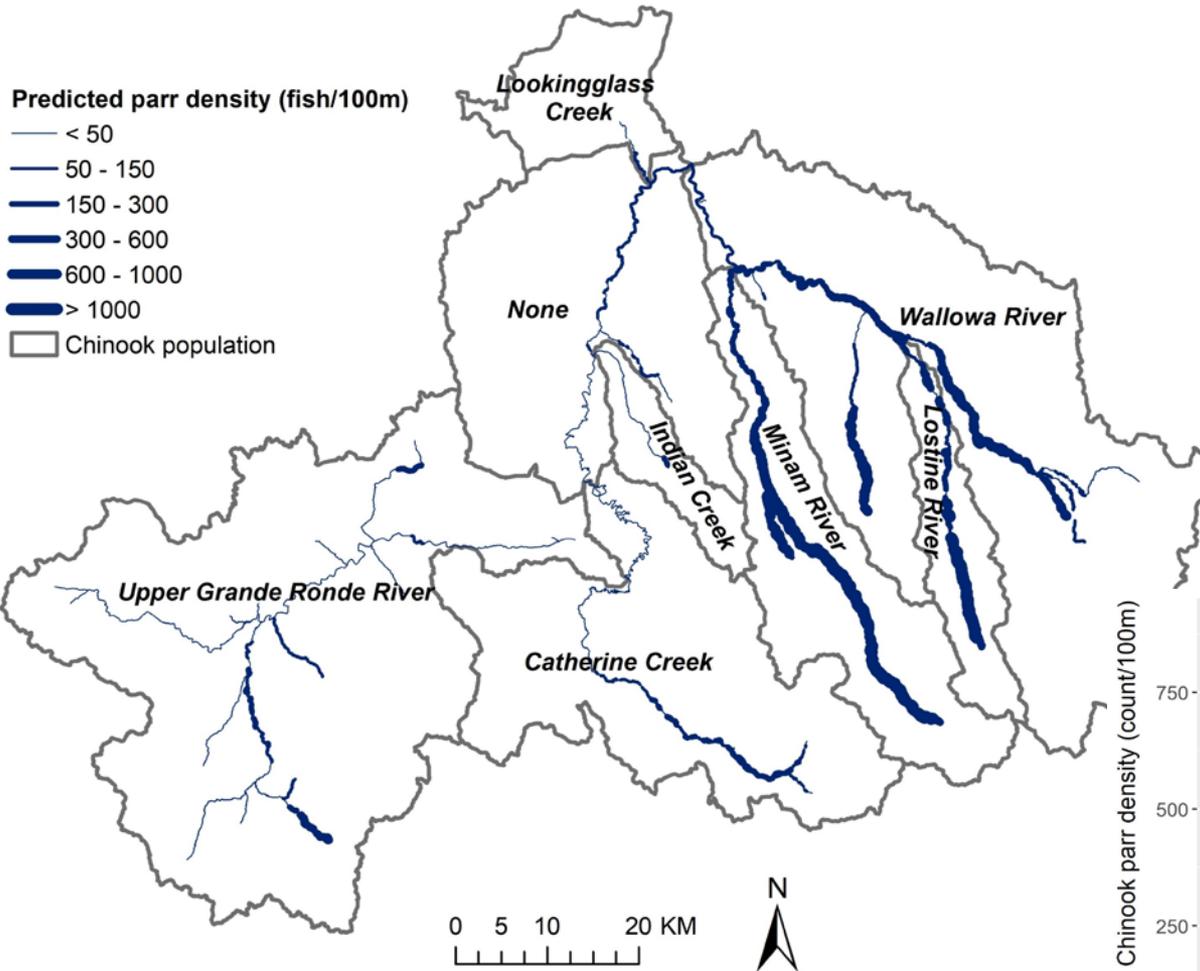
NOAA's National Water Model (1993-2018)

- Mean summer flow (Jun-Sep; cms)

NetMap (Benda et al. 2007)

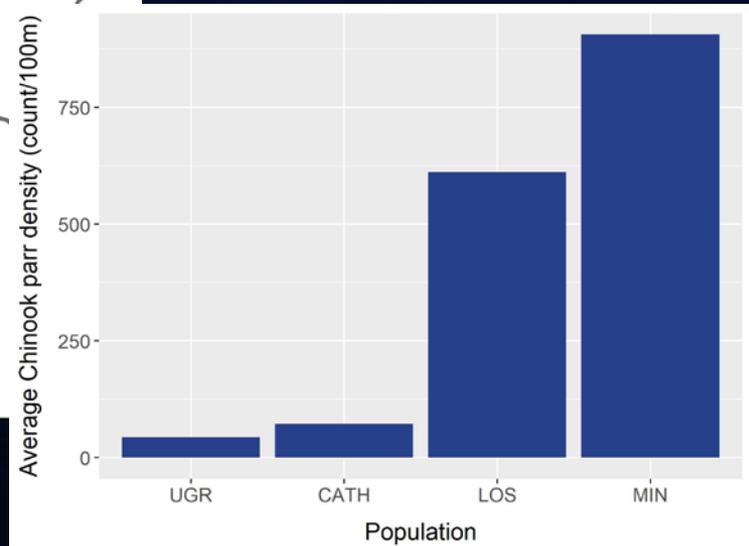
- Gradient

Density Predictions Across the Stream Network



Current Conditions Scenario:

- Recent 10-year mean flow and temperature
- Most recent measurements from Aquatic Inventories Data
- Spawner abundance set to 2 SD's above the mean to better reflect capacity



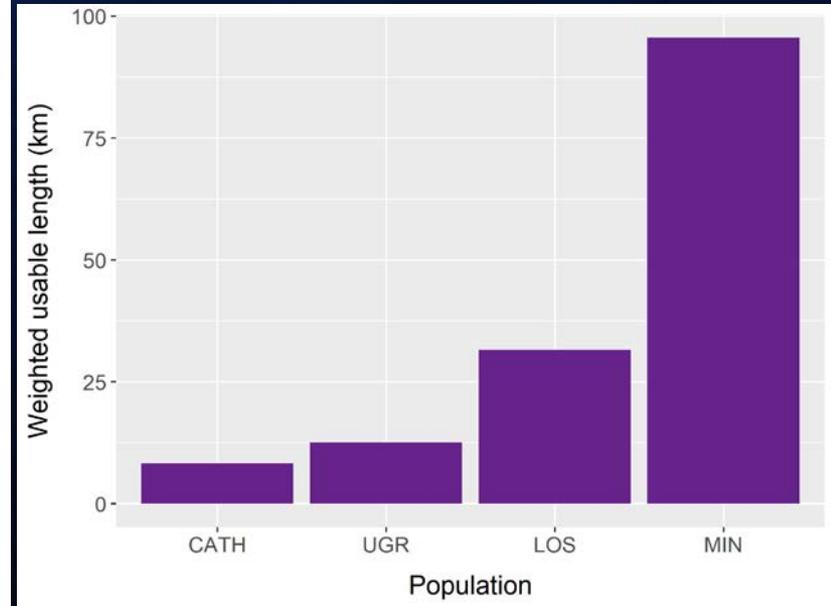
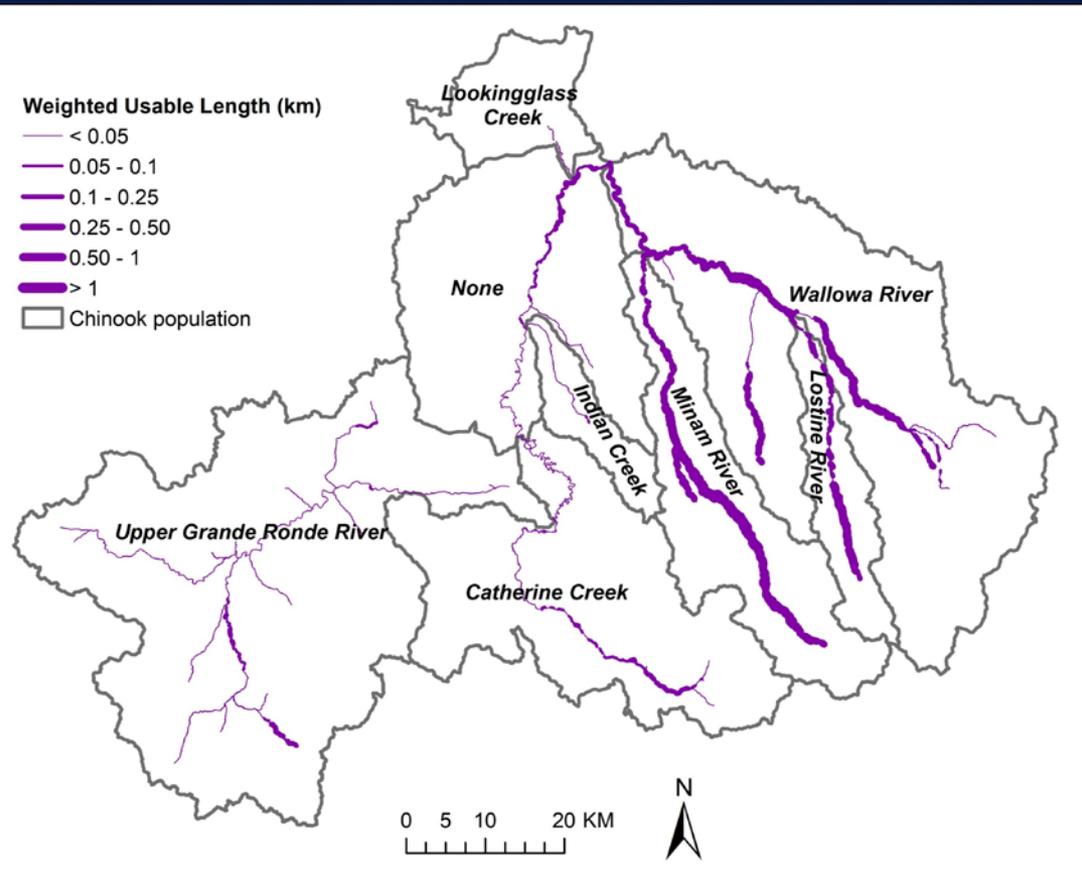
Translating Density Predictions into Weighted Usable Habitat

$$Weight_i = \frac{\text{Predicted parr density}_i}{\text{Max parr density}_i}$$

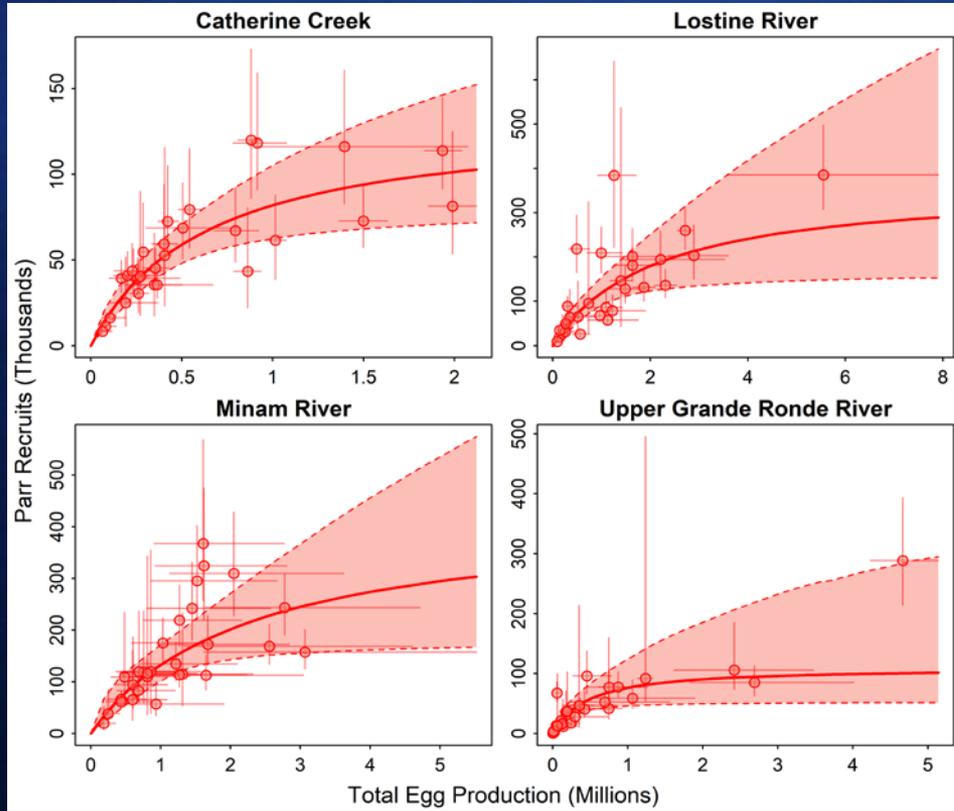
$$\text{Weighted usable length}_i (WUL_i) = Weight_i \times \text{Stream Length}_i$$

$$\text{Total WUL} = \sum_i^n WUL_i$$

$i = \text{reach}$



Linking Weighted Usable Habitat with Capacity



- Parr capacity was estimated within a multi-stage life cycle model using a 29-year time series of spawner and parr abundance data collected by ODFW and CTUIR (1991-2019).
- The LCM expresses parr capacity as a function of WUL
- Based on the contrast among the 4 populations, we can derive an estimate of $\Delta\text{capacity}/\Delta\text{WUL}$

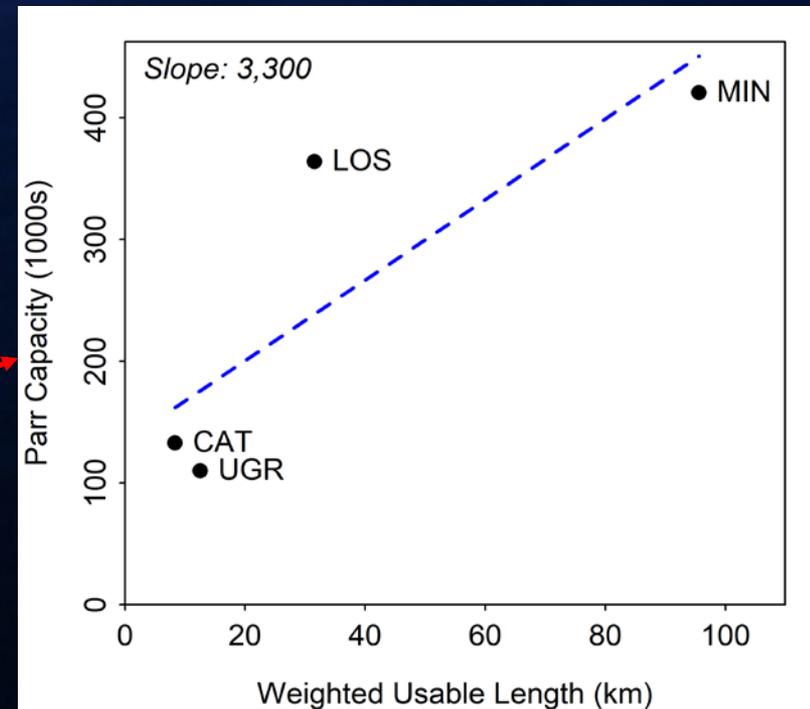
Beverton-Holt Model

$$Parr_{p,y} = \frac{Eggs_{p,y}}{\left(\frac{1}{prod_p} + \frac{Eggs_{p,y}}{cap_p}\right)} e^{\epsilon_{p,y}}$$

p = population

y = year

Δ = "change in"



Conclusions

- 1) Analysis of local empirical snorkel and habitat survey data revealed clear, biologically plausible, and statistically significant relationships between Chinook parr abundance and stream habitat conditions that are relevant to stream restoration.
- 2) Spatially-continuous covariate data such as that provided by the ODFW Aquatic Inventories program (or other rapid assessment methods), NorWeST, National Water Model and others provide a clear means of extrapolating fish predictions to larger scales as needed for population modeling and management decisions.
- 3) We developed a weighted usable habitat metric that is defensible, based on local empirical data, and can be integrated with life cycle models to project impacts of restoration, climate change, or other management scenarios on salmon populations.